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Impact of reliability parameters on O&M cost and greenhouse gas emissions of offshore wind farms

Moritz Gräfe[1], Samuel Kainz[2], Azélice Ludot[1], Vasilis Pettas[1], Abhinav Anand[2], Carlo L. Bottasso[2]

[1]DTU Wind and Energy Systems, Technical University of Denmark, Frederiksborgvej 399, Roskilde 4000, Denmark
[2]Wind Energy Institute, Technische Universität München, Boltzmannstr. 15, 85748 Garching bei München, Germany

E-mail: mograf@dtu.dk

Abstract. This study examines the impact of reliability parameters of critical turbine components on offshore wind farm operation and maintenance (O&M) costs and related greenhouse gas (GhG) emissions. Employing a simulation-based sensitivity analysis, we assess how variations in reliability parameters influence key O&M metrics, including total costs, component-specific breakdowns, availability, intervention frequency, and vessel usage. The associated climate impact is quantified based on vessel fuel consumption and spare part usage. The analysis uses data from the offshore wind farm Lillgrund, incorporating extensive SCADA data and real environmental conditions. For a variation of the reliability parameters by $\pm 50\%$, results indicate a total variation of up to $\pm 15\%$ in operational expenditures in absolute terms and per MWh of produced electricity. The impact of failure rates on CO_2-equivalent emissions is observed to be around $\pm 50\%$ relative to the baseline case for individual components, highlighting the significant influence of reliability on both costs and emissions. These findings underscore the importance of incorporating O&M processes in assessing the GhG footprint of wind energy and establishing a link between turbine reliability and emissions. Additionally, research gaps are identified in understanding the relationship between load conditions and component failure behavior, particularly in the context of wind farm control strategies.

1 Introduction

As offshore wind energy has become a fundamental part of the energy system and wind farms (WFs) operate in increasingly competitive market environments, optimizing their operational performance is increasingly important. While operators aim to minimize costs and maximize revenue, society is particularly interested in reducing the greenhouse gas (GhG) footprint of electricity production.

Both aspects are strongly influenced by the operation and maintenance (O&M) phase of wind energy production. O&M costs typically account for approximately 30% of the total cost of offshore wind energy production, making it one of the primary cost drivers [1]. Similarly, O&M-related GhG emissions contribute significantly to the overall carbon footprint of offshore wind projects. As reported in [2], estimates of O&M-related emissions vary between 5% and 30%, depending on wind farm specific modeling assumptions and the level of detail considered. A recent study incorporating vessel-related emissions estimated that O&M activities contribute 28% of the total GhG emissions for a hypothetical 740 MW wind farm off the coast of the Netherlands [3].

The reliability of wind turbine components and the associated maintenance requirements are key factors in determining both costs and emissions, as they influence the frequency of component failures and the maintenance processes required to address them. Maintenance activities typically involve vessel transportation, specialized equipment, spare parts, and labor. Reliability is defined as the probability that a component does not fail within a given time interval, which is primarily determined by its failure rate - a statistical measure of the number of failures occurring over time.

Several factors can influence the failure rates of specific components. Wind farm control strategies, which address aerodynamic interactions between turbines or implement electrical control approaches such as power boosting, can introduce unexpected load patterns not considered in the original system design [4]. These altered load patterns may positively or negatively affect component reliability. Other contributing factors include design flaws, manufacturing defects, and improper installation. Determining failure rates remains challenging and is often associated with significant uncertainties. This study aims to improve understanding of these uncertainties and their impact on cost and GhG emissions estimations.

The remainder of this paper is structured as follows: Section 2 provides an overview of existing studies and datasets quantifying the reliability of offshore wind turbine components. Section 3 introduces a workflow for assessing these impacts using operational data from an existing offshore wind farm and an O&M simulation tool that models the maintenance process in a time-marching manner. In section 4, the workflow is then demonstrated using the Lillgrund wind farm in the Baltic Sea as a case study. Finally, Section 5 discusses potential deviations from expected reliability and identifies key research gaps for future investigations.

2 Reliability data

The analysis of wind turbine reliability data presents several challenges, as outlined in the IEA Wind TCP Task 33 report [5] and supported by other studies. Operators often face difficulties in data collection, leading to poor data quality [6]. Additionally, the lack of standardized methods for O&M reporting, including systematic descriptions of affected components, failure modes, and failure definitions, further complicates reliability assessments [7]. Variability in failure classification by assembly adds another layer of complexity, making cross-study comparisons challenging [6, 8]. Limited collaboration among industry stakeholders, such as operators, manufacturers, and component suppliers further prevents data harmonization. Finally, ensuring that existing datasets accurately reflect modern turbine technology remains an ongoing challenge.

Thus, publicly available failure data for offshore wind farms is limited. While industry-owned databases offer insights into offshore risks, they are generally inaccessible due to confidentiality restrictions. In fact, open-access data is limited to three main sources, which are described in more detail below UK Round 1 offshore wind farms [9], Strathclyde database [10], and the reliability analysis of the Egmond aan Zee wind farm [11].

Under the “Offshore Wind Capital Grants Scheme,” UK Round 1 offshore wind farms were required to report operational data between 2004 and 2007. Feng et al. [9] analyzed these reports to extract lessons from early offshore wind operations, presenting findings on capacity factors, availability, and energy costs. Although failures and downtimes are discussed, no statistical failure analysis is provided. The dataset includes four wind farms, 120 turbines, totaling 300 MW and 270 operational years.

Operational reports from the Egmond aan Zee offshore wind farm in the Netherlands are available for the first three years of operation [11]. This wind farm consists of 36 Vestas V90-3MW wind turbines located 10–18 km offshore in the North Sea. The reports provide data on the number of stops caused by 13 sub-assemblies. However, the farm faced significant operational issues during its initial years, making these figures unrepresentative for use in a lifetime study.

Carroll et al. [10] published one of the most comprehensive datasets on reliability, referred to as the Strathclyde database, covering approximately 350 offshore wind turbines from a single manufacturer. The turbines have a nominal power between 2 MW and 4 MW and are between three and ten years old. What distinguishes this database from others is its detailed failure definitions, as well as insights into repair times, material costs, and the number of technicians required per subassembly. The study differentiates between minor and major repairs, as well as major replacements, providing comprehensive data for use in O&M cost models.

The limited availability of reliability data, particularly for specific turbine types and environmental conditions, introduces significant uncertainty in studies quantifying O&M costs and greenhouse gas emissions. Future research should prioritize improving access to operational data for statistical analysis and establishing links between technical, operational, and environmental factors affecting reliability.

3 Methodology

Figure 1 illustrates the methodology of this study, which is applied to the Lillgrund wind farm wind farm in the Baltic Sea. The characteristics of this wind farm, including layout, distance to port, vessel availability, metocean conditions, and turbine-specific power curves, are defined in Section 3.2. Reliability parameters for individual turbine components are derived from baseline values reported in the literature, with parameter variations applied as specified in Section 3.2. To account for seed-to-seed variability in individual simulation runs, 10 random realizations are generated for each simulation case.

The input parameters, including reliability parameters, simulation setup, and random seed, are then provided to the simulation tool WOMBAT [12], which models the operation and maintenance process, including failure occurrences, repair procedures, and turbine availability.

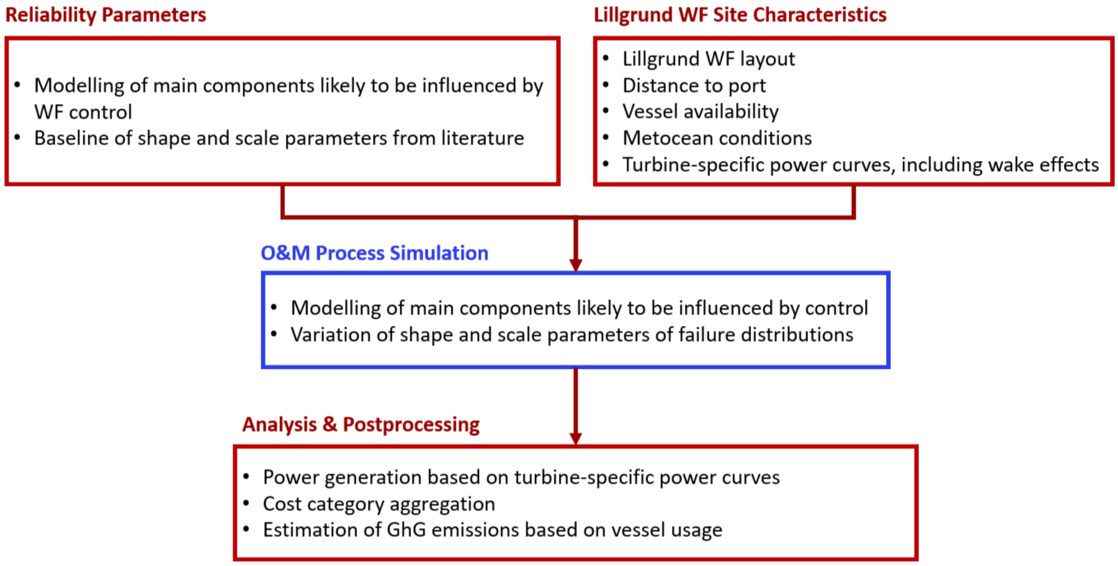


Figure 1: Methodology overview.

The modeled event chain begins with the sampling of failure times for each component and failure mode. When the simulation time reaches a component failure, the maintenance process is initiated. This process involves requesting the necessary resources (e.g., vessels, spare parts), assigning tasks to available resources, conducting maintenance activities, and restoring the operational status of the affected component. During this process, turbine downtime is accumulated, and O&M costs are tracked.

In WOMBAT, failure occurrences are modeled using a two-parameter Weibull distribution, which defines the probability of failure as a function of time. The scale parameter, λ, determines the failure rate, while the shape parameter, β, characterizes its variation over time: $\beta < 1$ indicates a decreasing failure rate, $\beta = 1$ represents a constant failure rate, and $\beta > 1$ corresponds to an increasing failure rate. A separate Weibull distribution is defined for each component and failure mode, with failure occurrences sampled independently. Each modeled component has three distinct failure modes - minor repair, major repair, and replacement - each characterized by specific parameters, including repair time, equipment requirements, and spare part costs. Lastly, the simulation results are postprocessed to determine the relevant key performance indicators. Electricity production is calculated using the site-specific met-ocean data time series, the availability time series from the O&M simulation, and the power curves of the individual turbines. The tracked O&M activities are translated into discounted OPEX via vessel-specific equipment rates, labor rates and failure-specific material costs.

3.1 O&M emissions

The GhG emissions related to the O&M activities over the plant lifetime are determined through post-processing of the WOMBAT model outputs. Three types of emission sources are considered: vessel fuel consumption, vessel production and maintenance, and spare part usage. To determine the emissions related to the fuel consumption during all O&M vessel activities, the total vessel hours for the involved vessel types are aggregated across their operational states transit, idle at site, and idle at port, with no emissions considered for the latter. The fuel consumption per hour for each vessel type and operational state is estimated following the methodology proposed by ref. [13], except for the fuel rates of the Crew Transfer Vessel for transit, taken from ref. [14], and for idling at site that are scaled according to assumptions in ref. [13]. Fuel consumption is considered for both heavy fuel oil (HFO) and marine gas oil (MGO). The associated GhG emissions are then calculated using wake-to-wake CO_2-equivalent (CO_2eq) emission factors from ref. [15], ensuring a comprehensive assessment of the climate impact of O&M vessel operations over the plant lifetime.

The GhG emissions related to vessel production and maintenance are estimated with two reference datasets for barge production and barge maintenance extracted from the *ecoinvent* database v3.8 [16], using the 'Allocation cut-off by classification' system model. The aggregated total vessel usage hours are normalized with the assumed vessel lifetime of 25 years associated to the datasets, and subsequently multiplied with the climate change impact factor of the two reference activities, resulting in the GhG emissions related to the vessel production and maintenance. Due to lack of specific data, different vessel types are not distinguished.

Finally, the emissions associated with spare parts are calculated based on the life-cycle emissions of the original components from cradle to grave, excluding installation, which is already accounted for in vessel emissions. The emissions related to spare parts are allocated using a cost-based approach, where emissions are scaled by the ratio of material costs for repair and replacement activities to the costs of the original components. Both the life-cycle emissions and original component costs are determined using the DETECT toolchain [3], applied to the Lillgrund wind turbine specification.

3.2 Lillgrund case study

Lillgrund is Sweden's largest offshore wind farm, located approximately 10 km off the southern coast of Sweden. It consists of 48 SWT 2.3 MW wind turbines, each with a rotor diameter of 93 m and a hub height of 65 m. The turbines are placed in a densely spaced layout, with an average inter-turbine distance of 3-5 rotor diameters (see Figure 2), leading to strong wake interactions.

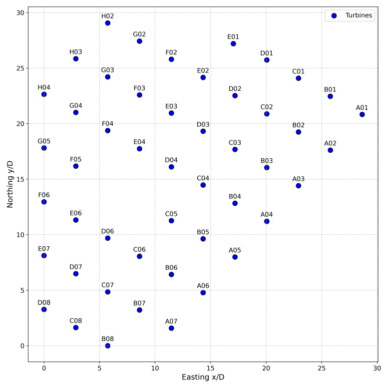


Figure 2: Lillgrund wind farm layout.

To account for these wake effects, the power curve of each turbine was determined for discrete wind direction sectors using SCADA data provided by the operator for a three-year period (2019-2022). Specifically, one power curve was generated for each 30° sector for every turbine. In the post-processing stage, these sector-averaged power curves were input into the WOMBAT framework to calculate the overall power production of the wind farm based on hourly mean wind speed and wind direction.

The following procedure was employed to derive the sector-specific power curves. First, the raw high-frequency data were checked and resampled to 10-minute statistics. These statistics were then filtered using the FLASC [17] framework, applying filters on power, pitch, and rotor parameters to retain only normal operating conditions. From the filtered dataset, farm-wide wind speed and direction were obtained by averaging the free-stream turbines' measurements for each wind direction. Using these aggregated wind speed and direction signals, the power curves for each turbine and sector were extracted, thereby incorporating operational wake losses. Figure 3 shows an example of such sector-averaged power curves.

Metocean data for the considered 20-year operational period (2004-2023) were obtained from ERA5 reanalysis at the wind farm location, providing hourly time series of wind speed, wind direction, and significant wave height. Figure 4 illustrates the wind and wave conditions distributions for the site over the entire period.

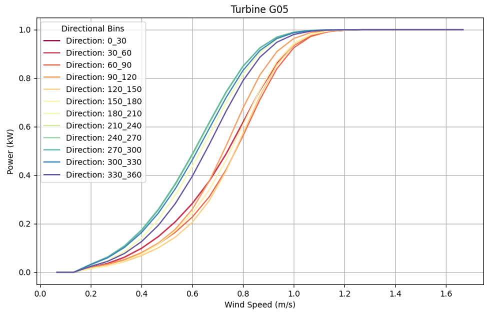
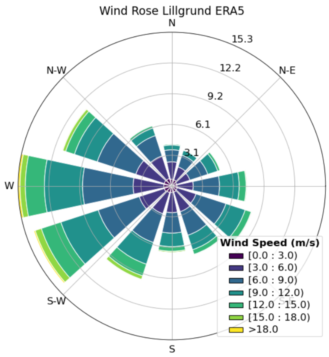
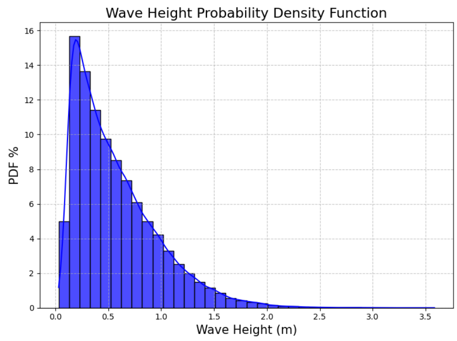


Figure 3: Example of directional power curve extracted from SCADA data for the G05 turbine. Values are normalized due to confidentiality



(a) Windrose Lillgrund wind farm



(b) Wave height probability density function

Figure 4: Windrose and wave height probability density function.

The simulation parameters and settings for the O&M process simulation are set to reflect the characteristics of the Lillgrund wind farm. Where the detailed characteristics of the actual process parameters are unknown, the chosen values are based on assumptions. Table 1 summarizes the main simulation parameters.

Parameter	Value
Operational life	2004 to 2024
Discount rate	0.045
Workday	7h to 19h
Distance to port	10km
Annual service	60 h/turbine
Service vessel type	CTV

Table 1: Simulation parameters.

Pivotal for the cost and emission implication of reliability are the characteristics of vessels used for maintenance tasks. Table 2 summarizes the assumed parameters of the three vessel types, including their fuel consumption and their specific CO_2eq emissions.

Table 3 shows the baseline failure rates for the selected components considered in the case study. The reported baseline failure rates are taken from existing literature. Our study varies these failure rates with a range of -50% to +50% from the baseline values, while the failure rates of all components and failure modes varied simultaneously. The shape parameter of the failure probability distribution, β, is set to one, which represents a constant failure rate over time. It should be noted that different assumptions for β can lead to a significantly different total number of failures during the project lifetime. However, the

Vessel type	**CTV**	**FSV**	**HLV**
Nr. of vessels	2	1	2
Strategy	continuous	continuous	chartered[1]
Equipment rate [€/day]	2,410	13,082	206,550
Nr. of technicians	3	4	5
Labor rate [€/h]	75	75	75
Max. wind speed [m/s]	-	-	10
Max. wave height [m]	1.5	1.5	2
Speed [km/h]	37.0	22.2	20.4
Fuel type	HFO	MGO	MGO
Fuel emissions [kgCO_2eq/kg]	4.05	4.26	4.26
Fuel rate at port [kg/h]	0	0	0
Fuel rate travel [kg/h]	101.7	304.0	418.0
Fuel rate at site [kg/h]	38.1	114.0	156.8

[1] Chartered for 20 days as soon as three replacement requests accumulate. Foregoing mobilization time of 10 days with mobilization cost of 325,000€.

Table 2: Vessel parameters for crew transfer vessels (CTV), field-support vessels (FSV) and heavy lift vessels (HLV) based on ref. [12–14, 18, 19].

trends in costs and emissions from changing failure rates are not significantly modified for different shape parameters. All results are reported in steps of 10% deviation from the baseline failure rate. The failure rates are applied for all turbines in the wind farm uniformly.

Component	**Minor**[1]	**Major**[1]	**Replacement**[1]	**Range**
Blade	0.456	0.01	0.001	-50% to +50%
Pitch	0.824	0.179	0.001	
Yaw Bearing	0.162	0.006	0.001	
Gearbox	0.305	0.0338	0.042	
Generator	0.473	0.036	0.008	
Power Electronics	0.076	0.081	0.005	
Tower	0.092	0.089	0	

[1] Unit: *failures/turbine/year*

Table 3: Failure categories for selected components and baseline failure rates taken from [4, 10].

4 Results

Figure 5 presents the O&M costs throughout the project lifetime for the components specified in Table 3, considering failure rates ranging from -50% to +50% relative to the baseline (0%) failure rates. The individual bars represent the mean simulation results across all random seeds.

Costs are categorized into three groups: material costs, equipment costs, and labor costs. While an increase in failure rates affects all components, certain components contribute disproportionately to overall costs. These components are characterized by high baseline failure rates and high material and equipment costs. Under the assumptions of this study, and based on baseline failure rates derived from the literature, the gearbox accounts for the largest share of O&M costs. This is primarily due to the high cost of spare parts and the necessity of heavy-lift vessels for major replacements.

Figure 6 presents the total project OPEX and OPEX per unit of produced electricity for varying failure rates. The boxes represent the variability of results across all random seeds. The simulated total project OPEX ranges from approximately 145 M€ to 190 M€, corresponding to OPEX costs between 17 and 24 €/MWh across the full range of reliability variations. This highlights the potential for substantial increases or reductions in O&M costs as a result of changes in failure rates. The study demonstrates a total variation of approximately $\pm$15% in operational expenditures, both in absolute terms and relative to the amount of electricity produced. While a 50% increase in all failure rates, potentially caused by

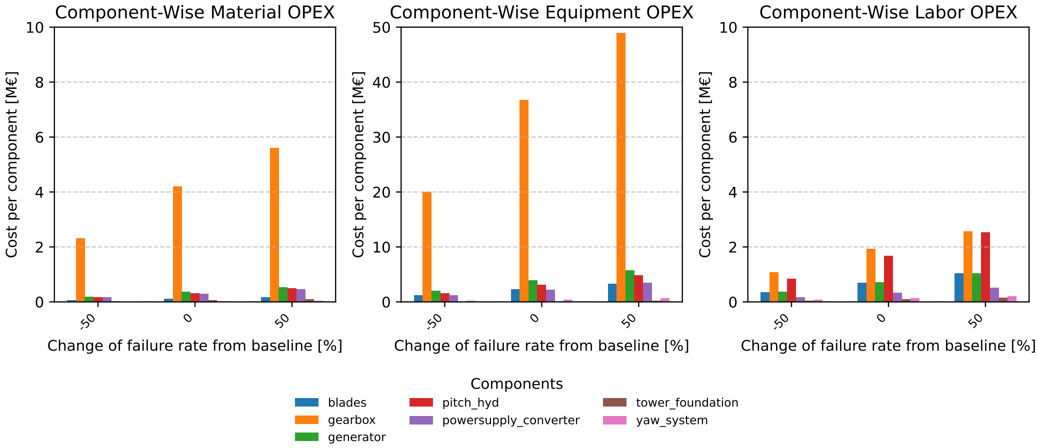


Figure 5: Component-wise break down of O&M costs.

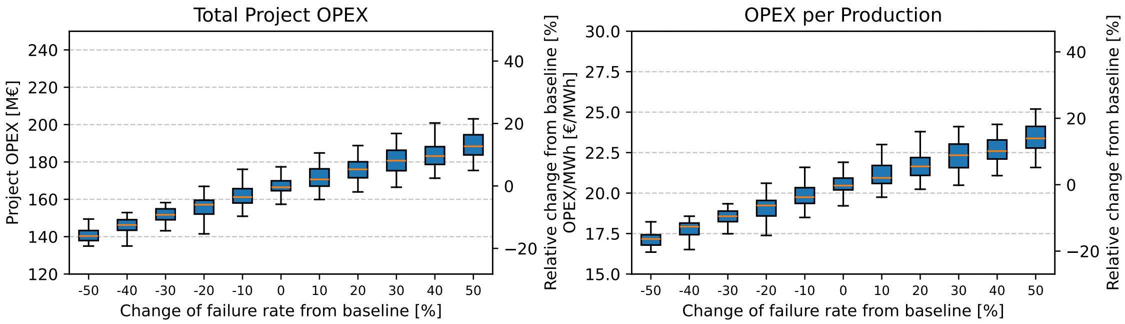


Figure 6: Total OPEX (left) and OPEX per production (right).

factors such as changing load patterns, component quality, or installation issues, represents an extreme case, the results underscore the significance of failure rate variations in determining OPEX.

Figure 7 presents time-based and production-based availability as a function of changing failure rates. Time-based availability represents the proportion of technically available time relative to the total operational time, while production-based availability denotes the share of electricity produced relative to the theoretical maximum production without downtime. In contrast to the high variability observed in O&M costs, the sensitivity of availability to failure rates is relatively low, with variations of approximately $\pm 2\%$. It is important to note that these results assume the continuous availability of materials, equipment, and workforce. In practice, delays in spare part supply or vessel unavailability could lead to extended downtimes per failure, thereby amplifying the impact on availability.

Figure 8 illustrates the CO_2-equivalent emissions associated with different components over the range of failure rate variations. Emissions are categorized into vessel-related emissions (center) and material-related emissions (right). Vessel-related emissions include those resulting from fuel combustion and vessel operation and maintenance, while material-related emissions represent the life-cycle emissions of spare parts. Total emissions correspond to the sum of both categories.

The impact of failure rates on CO_2-equivalent emissions is observed to be approximately $\pm 50\%$ relative to the baseline case for individual components. Notably, the components responsible for the highest costs do not necessarily contribute the most to CO_2-equivalent emissions. While high costs are primarily driven by expensive materials, equipment, and labor (e.g., the gearbox), vessel-related emissions may be more significantly influenced by frequent but relatively low-cost minor repair activities.

This finding is further supported by Figure 9, which presents vessel-related emissions for the three vessel types used under varying failure rates. The results indicate that crew transfer vessels, primarily utilized for minor repair tasks, contribute the most to overall vessel emissions. In contrast, heavy-lift vessels and field support vessels, which are required for major repairs and replacements such as gearbox

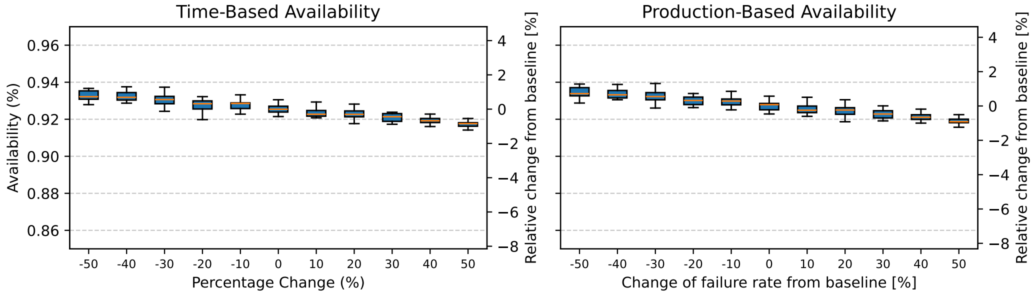


Figure 7: Time-based availability (left) and production based availability (right).

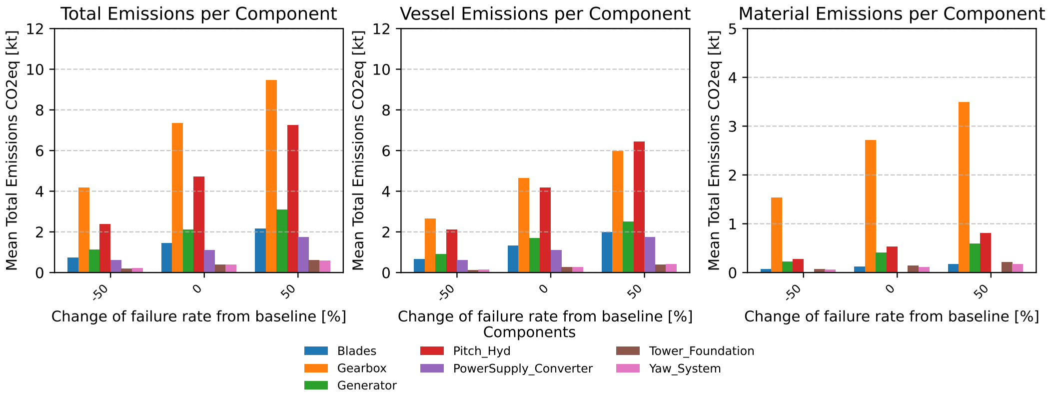


Figure 8: Greenhouse gas emissions per component.

replacements, result in lower total CO_2-equivalent emissions.

5 Discussion

Our study demonstrates the general impact of varying failure rates on O&M costs and greenhouse gas emissions. However, the analysis relies on several assumptions regarding the characteristics of the maintenance process, associated costs, and emissions. More accurate data on the actual reliability of components in the investigated wind farm would be required to reduce uncertainty in the results. Therefore, the findings of this study should be interpreted as indicative of trends and orders of magnitude rather than precise predictions. Furthermore, this study does not investigate the underlying causes of deviations from expected component reliability.

Deviations from expected component reliability can arise from various root causes and physical phenomena. Potential causes of unexpected reliability issues include design flaws, manufacturing defects, quality control issues, and improper installation. In such cases, reliability deviations may occur independently of changes in the expected load patterns. Another source of reliability deviations may stem from variations in operational structural load patterns, which can lead to variations in fatigue damage accumulation and actuator wear and tear. These variations can be influenced by operational decisions such as the application of wind farm control strategies. Unlike conventional ”greedy” control strategies that optimize individual turbine performance, wind farm control aims to optimize the operation of the entire wind farm. This is achieved through wind farm flow control, which mitigates aerodynamic interactions among turbines, and wind power plant control, which addresses electrical control objectives, such as grid service provision.

At the turbine level, wind farm control strategies include wake steering and induction control to minimize wake interactions, as well as power boosting and down-regulation to meet grid demands. These control actions can affect the load patterns on the individual components of each machine [20], potentially affecting reliability. However, these load pattern changes are not uniform across the wind farm. While some turbines may experience adverse effects, such as increased loads due to wake steering, downstream turbines may benefit from reduced wake interactions, resulting in more favorable load conditions.

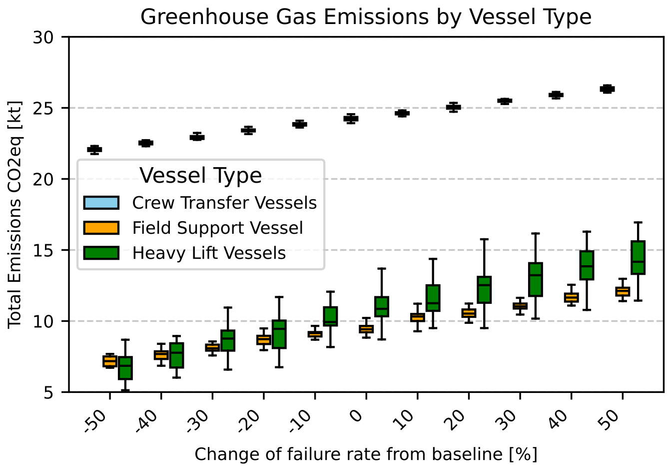


Figure 9: Greenhouse gas emissions by considered vessel type.

From this discussion, we identify two key research gaps, particularly in the context of WF control:

1. The distribution of wind farm control-induced changes in turbine load patterns across wind farms is not sufficiently understood, described, or quantified.
2. The relationship between load conditions and reliability parameters remains largely unknown.

Future research should address both gaps. Ongoing work in this area includes developing wind farm response models that incorporate control actions and turbine flow interactions. Approaches based on fatigue damage accumulation or physical modeling of degradation mechanisms may provide further insights into the relationship between load conditions and reliability.

6 Conclusions

Our study presents a workflow for assessing the impact of reliability parameters on O&M costs and GhG emissions using existing publicly available tools, while accounting for site-specific conditions and the performance of an operating offshore wind farm. The results indicate a total variation of approximately $\pm 15\%$ in operational expenditures compared to the baseline values, both in absolute terms and per MWh of produced electricity. Additionally, the impact of failure rates on CO_2-equivalent emissions is observed to be around $\pm 50\%$ relative to the baseline case for individual components, demonstrating a substantial influence of failure rates on both costs and emissions.

These findings emphasize the importance of incorporating O&M processes into assessing the carbon footprint of wind energy and establish a link between turbine and component reliability and emissions. Enhancing the reliability of key components or adopting more sustainable maintenance strategies, such as the use of low-emission vessels, could significantly reduce emissions. Furthermore, we identify research gaps in understanding the relationship between load conditions and component failure behavior, particularly in the context of wind farm control activities.

Acknowledgements

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